Design of Optimal Linear Phase FIR High Pass Filter using Improved Particle Swarm Optimization

Sangeeta Mandal[1], S.P.Ghoshal[1], Purna Mukherjee[2], Dyuti Sengupta[2], Rajib Kar[2], Durbadal Mandal[2]
[1] Department of Electrical Engg.
National Institute of Technology, Durgapur, West Bengal, INDIA
[2] Department of Electronics and Communication Engineering
National Institute of Technology, Durgapur, West Bengal, INDIA
rajibkarece@gmail.com

***Abstract*— This paper presents a novel approach for designing a linear phase digital high pass FIR filter using Improved Particle Swarm Optimization (IPSO) algorithm. Design of FIR filter is a multi-modal optimization problem. The conservative gradient based optimization techniques are not efficient for digital filter design. Given the specifications for the filters to be realized, IPSO algorithm generates a set of optimal filter coefficients and tries to meet the ideal frequency response characteristics. This paper presents the realization of the optimal FIR high pass filter of filter order 20 as per given problem statements. The simulation results have been compared to those obtained from well accepted classical algorithms like Park and McClellan algorithm (PM), and evolutionary algorithms like genetic algorithm (GA) and particle swarm optimization (PSO). The results rationalize that the proposed optimal filter design approach using IPSO outperforms PM, RGA, PSO in the accuracy of the designed filter, as well as in the convergence speed and solution quality.**

***Index Terms*— Parks and McClellan Algorithm, RGA, PSO, IPSO, Evolutionary Optimization Technique, Convergence, High Pass Filter, FIR Filter**

I. Introduction

Digital Signal Processing (DSP) presents greater flexibility, higher performance (in terms of attenuation and selectivity), better time and environment stability along with lower equipment production costs than traditional analog techniques. Additionally, more and more microprocessor circuits are being substituted with cost effective DSP techniques and products. DSP has a wide range of applications in the fields of communication, image processing, pattern recognition, etc. These new DSP applications result from advances in digital filtering. A digital filter is simply a discrete-time, discrete-amplitude convolver.

There are two basic types of digital filters, Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filters. FIR digital filter have many advantages such as guaranteed stability, free from phase distortion and low coefficient sensitivity. There have been considerable amount of works on the design of computationally efficient FIR digital filters [1-2] and their corresponding hardware implementations [3-4].An optimization technique based on Remez Exchange algorithm proposed by Parks and McClellan is one of the most prominent ones and provides a speed advantage over the linear programming approach.In order to design FIR filters with a given stop band deviation, filter length and cut-off frequency, the program needs several iterations [6]. A number of models have been developed for the FIR filter techniques and design optimization methods. Different heuristic optimization algorithms such as simulated annealing algorithms [7], genetic algorithm (GA) [8], artificial bee colony algorithm [9], etc. have been widely applied for the synthesis of filter design methods capable of satisfying certain constraints. Genetic algorithms (GA) have surfaced as prominent design and optimization methods of FIR digital filters, particularly due to their ability to automatically find near-optimum solutions while maintaining the computational complexity of the algorithm at moderate levels. The only difficulty with RGA arises in terms of convergence speed and quality of the solution obtained.

The approach detailed in this paper takes advantage of the power of the stochastic global optimization technique called particle swarm optimization. Particle Swarm Optimization (PSO) is an evolutionary algorithm developed by Eberhart *et al*. [10-11]. Several attempts have been made towards the optimization of the FIR Filter [12] using PSO algorithm. The PSO is simple to implement and its convergence may be controlled via few parameters. The limitations of the conventional PSO are that it may be influenced by premature convergence and stagnation problem [13-14]. In order to overcome these problems, the PSO algorithm has been modified in this paper and is employed for FIR high pass filter design.

This paper describes a novel technique for the FIR high pass digital filter design using improved particle swarm optimization approach (IPSO). IPSO algorithm tries to find the best coefficients that closely match the ideal frequency response. Based upon the IPSO approach, this paper presents a good and comprehensive set of results, and states arguments for the superiority of the algorithm. Simulation result demonstrates the effectiveness and better performance of the proposed designed method.

The rest of the paper is arranged as follows. In section II, the FIR high pass filter design problem is formulated. Section III briefly discusses on the algorithms of RGA, classical PSO and the IPSO algorithm. Section IV describes the simulation results obtained for high pass FIR digital filter using PM algorithm, RGA, PSO and the proposed IPSO approach. Finally, section V concludes the paper.

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II. High Pass FIR Filter Design

Digital filters are classified as finite impulse response (FIR) or infinite impulse response (IIR) filter depending upon whether the response of the filter is dependent on only the present input values or on the present inputs as well as previous outputs, respectively.

A finite-duration impulse response filter has a system function of the form given in (1).

$$H(z) = h(0) + h(1)z^{-1} + ... + h(N)z^{-N} \quad (1)$$

or, $$H(z) = \sum_{n=0}^{N} h(n)z^{-N} \quad (2)$$

where h(n) is called impulse response. The diference equation representation is

$$y(n) = h(0)x(n) + h(1)x(n-1) + ... + h(N)x(x-N) \quad (3)$$

The order of the filter is N, while the length of the filter (which is equal to the number of coefficients) is N+1. The FIR filter is always stable, and can be designed to have a linear phase response. The impulse response h(n) is to be determined in the design process and the values of h(n) will determine the type of the filter e.g. low pass, high pass etc. The choice of the filters is based on three broad criteria, namely, the filters should: Provide zero distortion to the signal; Flat pass band; Exhibit highest attenuation characteristics in the stop band.

Other desirable characteristics include short filter length, short frequency transition beyond the cut off point, and the ability to manipulate the attenuation in the stop band.

In this paper, IPSO is applied in order to obtain the actual filter response as close as possible to the ideal response. In each iteration, these individuals are updated. Fitnesses of particles are calculated using the new coefficients. The result obtained after a certain number of iterations or after the error is below a certain limit is considered to be the optimal result. The error for this fitness function is the difference between the magnitudes of the ideal filter and the filter designed using the evolutionary algorithms like RGA, PSO and IPSO. The individuals that have lower error values represent the better filter i.e., the filter with better frequency response.

The frequency response of the FIR digital filter can be calculated as,

$$H(e^{jw_k}) = \sum_{n=0}^{N} h(n)e^{-jw_k n}; \quad (4)$$

where $\omega_k = \frac{2\pi k}{N}$; $H(e^{jw_k})$

is the Fourier transform complex vector. This is the FIR filter frequency response. The frequency in [0, π] is sampled with N points.Different kinds of fitness functions have been used in different literatures as given in (5) and (6) [15-19].

$$Error = \max\left\{\sum_{i=1}^{N}\left[\left|H_d(e^{jw_i})\right| - \left|H_i(e^{jw_i})\right|\right]\right\} \quad (5)$$

$$Error = \left\{\sum_{i=1}^{N}\left[\left|H_d(e^{jw_i})\right| - \left|H_i(e^{jw_i})\right|\right]^2\right\}^{1/2} \quad (6)$$

$$E(\omega) = G(\omega)\left[H_d(e^{j\omega}) - H_i(e^{j\omega})\right] \quad (7)$$

An error function given by (7) is the approximate error used in popular Parks–McClellan (PM) algorithm for digital filter design [5].

where $G(\omega)$the weighting function is used to provide different weights for the approximate errors in different frequency bands; $H_d(e^{j\omega})$ is the frequency response of the desired filter and in case of high pass filter

$$H_d(e^{j\omega_k}) = 1 \quad \text{for} \quad 1 \le \omega \le \omega_c; \quad = 0 \quad \text{otherwise} \quad (8)$$

where ω_c is the cut-off frequency of the filter to be designed and $H_i(e^{j\omega})$is the frequency response of the approximate filters [20].

The major drawback of the PM algorithm is that the ratio of $\ddot{a}_p/\ddot{a}_s$ is fixed. In order to improve the flexibility in the error function to be minimized, so that the desired level of $\ddot{a}_p$ and $\ddot{a}_s$ may be individually specified, the error function given in (9) has been considered as fitness function in [12], [18], although [18] shows zero improvement compared to the PM algorithm.

$$J_1 = \max_{\omega \le \omega_p}\left(\left|E(\omega)\right| - \delta_p\right) + \max_{\omega \ge \omega_s}\left(\left|E(\omega)\right| - \delta_s\right) \quad (9)$$

where δ_p and δ_s are the ripples in the pass band and the stop band; ω_p and ω_s are the pass band and stop band normalized edge frequencies, respectively.

In this paper, a novel error fitness function has been adopted in order to achieve higher stop band attenuation and to have an accurate control on the transition width. The fitness function used in this paper is given in (10). Using (10), it is found that the proposed filter deign approach results in considerable improvement over the PM and other optimization techniques.

$$J_2 = \sum abs\left[abs\left(\left|H(\omega)\right| - 1\right) - \delta_p\right] + \sum\left[abs\left(\left|H(\omega)\right| - \delta_s\right)\right] \quad (10)$$

For the first term of (10), $\omega \in$ pass band including a portion of the transition band and for the second term of (10), $\omega \in$ stop band including the rest portion of the transition band. The portions of the transition band chosen depend on pass band edge and stop band edge frequencies.

The error function given in (10) represents the generalized fitness function to be minimized using the evolutionary algorithms. The algorithms try to minimize this error and thus improve the filter performance. Since the coefficients of the linear phase filter are matched, the dimension of the problem is thus reduced by one-half. By only determining half of the coefficients, the filter can be designed. This greatly reduces the computational burdens of the algorithms, applied to the design of linear phase FIR filters.

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III. Evolutionary Techniques Employed

A. Real Coded Genetic Algorithm (RGA)

Steps of RGA as implemented for optimization of h(n) coefficients are adopted from [21-22]. In this work, initialization of real chromosome string vectors of n_p population, each consisting of a set of h(n) coefficients is made. Size of the set depends on the number of coefficients in a particular filter design.

B. Particle Swarm Optimization (PSO)

PSO is a flexible, robust population-based stochastic search/optimization technique with implicit parallelism, which can easily handle with non-differential objective functions, unlike traditional optimization methods. PSO is less susceptible to getting trapped on local optima unlike GA, Simulated Annealing etc. Eberhart *et al.* [10-11] developed PSO concept similar to the behavior of a swarm of birds. PSO is developed through simulation of bird flocking in multidimensional space. Bird flocking optimizes a certain objective function. Each particle (bird) knows its best value so far (pbest). This information corresponds to personal experiences of each particle. Moreover, each particle knows the best value so far in the group (gbest) among pbests. Namely, each particle tries to modify its position using the following information:

- The distance between the current position and the pbest.
- The distance between the current position and the gbest.

Similar to GA, in PSO techniques also, real-coded particle vectors of population n_p are assumed. Each particle vector consists of components or sub-strings as required number of normalized filter coefficients, depending on the order of the filter to be designed.

Mathematically, velocities of the particles are modified according to the following equation:

$$V_i^{(k+1)} = w * V_i^k + C_1 * rand_1 * \left(pbest_i^k - S_i^k\right) + C_2 * rand_2 * \left(gbest^k - S_i^k\right) \quad (11)$$

where V_i^k is the velocity of i[th] particle at k[th] iteration; w is the weighting function; C_1 and C_2 are the positive weighting factors; $rand_1$ and $rand_2$ are the random numbers between 0 and 1; S_i^k is the current position of i[th] particle at k[th] iteration; $pbest_i^k$ is the personal best of the i[th] particle at the k[th] iteration; $gbest^k$ is the group best of the group at the k[th] iteration. The searching point in the solution space may be modified by the following equation:

$$S_i^{(k+1)} = S_i^k + V_i^{(k+1)} \quad (12)$$

The first term of (11) is the previous velocity of the particle. The second and third terms are used to change the velocity of the particle. Without the second and third terms, the particle will keep on ''flying'' in the same direction until it hits the boundary. Namely, it corresponds to a kind of inertia represented by the inertia constant, w and tries to explore new areas.

A. Improved Particle Swarm Optimization (IPSO)

The global search ability of traditional PSO is very much enhanced with the help of the following modifications. This modified PSO is termed as IPSO [23].

i) The two random parameters $rand_1$ and $rand_2$ of (11) are independent. If both are large, both the personal and social experiences are over used and the particle is driven too far away from the local optimum. If both are small, both the personal and social experiences are not used fully and the convergence speed of the technique is reduced. So, instead of taking independent $rand_1$ and $rand_2$, one single random number r_1 is chosen so that when is large, is small and vice versa. Moreover, to control the balance of global and local searches, another random parameter is introduced. For birds flocking for food, there could be some rare cases that after the position of the particle is changed according to (11), a bird may not, due to inertia, fly toward a region at which it thinks is most promising for food. Instead, it may be leading toward a region which is in the opposite direction of what it should fly in order to reach the expected promising regions. So, in the step that follows, the direction of the bird's velocity should be reversed in order for it to fly back into promising region. is introduced for this purpose. Both cognitive and social parts are modified accordingly. Other modifications are described below.

ii) A new variation in the velocity expression (11) is made by splitting the cognitive component (second part of (11)) into two different components. The first component can be called *good experience component*. That is, the particle has a memory about its previously visited best position. This component is exactly the same as the cognitive component of the conventional PSO. The second component is given the name *bad experience component*. The bad experience component helps the particle to remember its previously visited worst position. The inclusion of the worst experience component in the behavior of the particle gives additional exploration capacity to the swarm. By using the bad experience component, the bird (particle) can bypass its previous worst position and always try to occupy a better position.

Finally, with all modifications, the modified velocity of the i[th] particle vector at the (k+1)[th] iteration is expressed as (13).

$$\begin{aligned} V_i^{(k+1)} &= r_2 * sign(r_3) * V_i^k + (1 - r_2) * C_1 * r_1 * \left\{pbest_i^k - S_i^k\right\} \\ &+ (1 - r_2) * C_2 * (1 - r_1) * \left\{gbest^k - S_i^k\right\} + (1 - r_2) * c_1 * r_1 \left(S_i^k - pworst_i^k\right) \end{aligned} \quad (13)$$

where $sign(r_3)$ is a function defined as:

$sign(r_3) = -1$ where $r_3 \le 0.05$; $= 1$ where $r_3 > 0.05$

V_i^k is the velocity of the i[th] particle at the k[th] iteration; r_1, r_2 and r_3 are the random numbers between 0 and 1; S_i^k is the current position of the i[th] particle at the k[th] iteration; $pbest_i^k$ and $pworst_i^k$ are the personal best and the personal worst of

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the i[th] particle respectively ; $gbest^k$ is the group best among all pbests for the group.The searching point in the solution space is modified by the equation (12) as usual.

IV. Results and Discussions

A. Analysis of Magnitude Response of High Pass Filters

In order to demonstrate the effectiveness of the proposed filter design method, FIR filter is constructed using RGA, PSO, IPSO algorithms. The MATLAB simulation has been performed extensively to realize the high pass FIR filter of the order of 20. Hence, the length of the filter coefficient is 21. The sampling frequency has been chosen as f_s = 1Hz. Also, for all the simulations the number of sampling points is taken as 128. Algorithms are run for 40 times to get the best solutions. The best results are reported in this work.

The parameters of the filters to be designed are: pass band ripple (δ_p) = 0.1, stop band ripple (δ_s) = 0.01. For high pass filter, pass band (normalized) edge frequency (ω_p) = 0.75; stop band (normalized) edge frequency (ω_s) = 0.65; transition width=0.1. Figure 1 shows the magnitude plot for the high pass FIR filter of the order of 20. The best optimized coefficients for the designed filters with the order of 20 have been calculated by RGA, PSO and IPSO and given in Table II. Table I shows the maximum stop band attenuation (dB), maximum pass band ripple (normalized), maximum stop band ripple (normalized) and transition width for all the aforementioned optimization algorithms. From the figure and tables, it is evident the proposed filter design approach IPSO produces higher stop band attenuation and smaller stop band ripple compared to that of PM, RGA and PSO.

The filter designed by the IPSO algorithm has a similar transition band response to that of the response produced by RGA, PSO algorithms. For the stop band region, the filters designed by the IPSO method results in the improved responses than the other.

B. Comparative effectiveness and convergence profiles

In order to compare the algorithms in terms of the convergence speed, Figures 2-4 show the plots of minimum error values against the number of iteration cycles when RGA, PSO and IPSO are employed, respectively. The convergence profiles have been shown for the filter order of 20.

From the figures drawn for this filter, it is seen that the IPSO algorithm is significantly faster than the RGA and PSO algorithms for finding the optimum filter. The IPSO converges to a much lower fitness in lesser number of iterations. Further,

PSO yields suboptimal higher values of error but IPSO yields near optimal (least) error values. With a view to the above fact, it may finally be inferred that the performance of IPSO technique is better as compared to RGA and PSO in designing the optimal FIR filter. All optimization programs are run in MATLAB 7.5 version on core (TM) 2 duo processor, 3.00 GHz with 2 GB RAM.

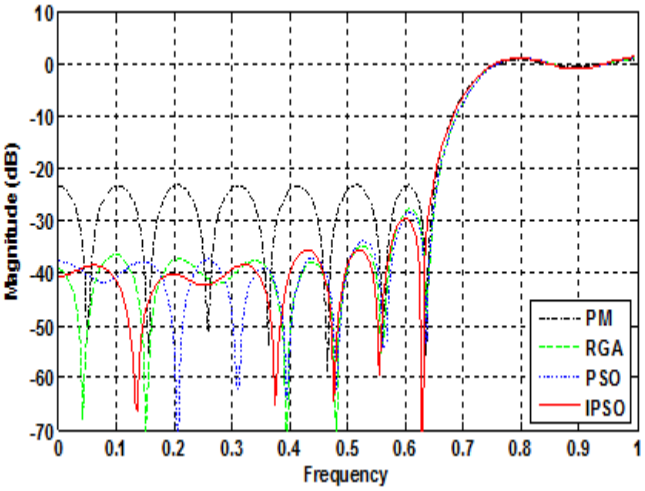


Figure 1. Magnitude (dB) Plot of the FIR High Pass Filter of Order 20.

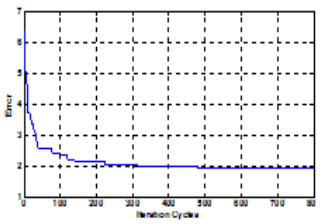


Figure 2. Convergence Profile for RGA in case of 20th Order HP FIR Filter.

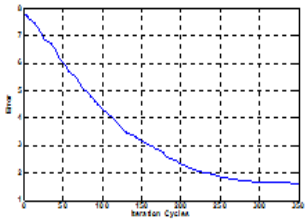


Figure 3. Convergence Profile for PSO for 20th order HP FIR Filters

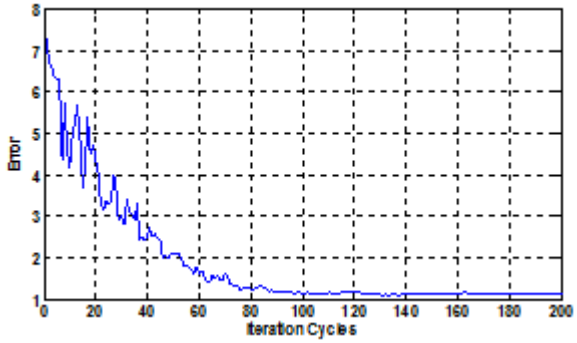


Figure 4. Convergence Profile for IPSO in case of 20th Order High Pass FIR Filters.

V. Conclusions

This paper presents a novel and optimal method for designing linear phase digital high pass FIR filters by using nonlinear stochastic global optimization based on IPSO. Filter of order 20 has been realized using RGA, PSO as well as with the proposed IPSO algorithm. Extensive simulation results justify that the proposed algorithm outperforms RGA and classical PSO in the accuracy of the magnitude response of the filter as well as in the convergence speed and is adequate for use in other related design problems.

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TABLE I. OTHER COMPARATIVE RESULTS OF PERFORMANCE PARAMETERS OF ALL ALGORITHMS FOR HIGH PASS FILTER

Algorithm	High Pass filter			
	Maximum stop band attenuation (dB)	Maximum pass band ripple (normalized)	Maximum stop Band ripple (normalized)	Transition width
PM	23.24	0.069	0.06888	0.0845
RGA	27.85	0.137	0.04049	0.0896
PSO	28.52	0.132	0.03752	0.0898
IPSO	29.59	0.147	0.03316	0.0924

TABLE II. OPTIMIZED COEFFICIENTS OF FIR HIGH PASS FILTER OF ORDER 20

h(N)	RGA	PSO	IPSO
h(1)=h(21)	0.017500201326591	0.016684532700955	0.014051882288068
h(2)=h(20)	-0.034664703361583	-0.037026662035285	-0.034948107822049
h(3)=h(19)	0.039675441442365	0.036919859322288	0.041566245350805
h(4)=h(18)	-0.011039969232810	-0.013338708349390	-0.018209649407699
h(5)=h(17)	-0.029877373263831	-0.030173799057269	-0.024453045297124
h(6)=h(16)	0.060407393938230	0.060619921506844	0.056569079961636
h(7)=h(15)	-0.045357174244925	-0.041732050291725	-0.048853500210415
h(8)=h(14)	-0.036529016628391	-0.033569883346433	-0.032039242781614
h(9)=h(13)	0.151333684873435	0.153153102550027	0.149742172523051
h(10)=h(12)	-0.256137892428781	-0.255126724552754	-0.260703666822173
h(11)	0.300174715164156	0.300174715164156	0.305283906116923

REFERENCES

[1] T. Parks and J. McClellan, "Cheyshev approximation for nonrecursive digital filters with linear phase." IEEE Trans. on Circuit Theory, vol. CT-19, pp. 189–194, 1972.

[2] Y. C. Lim, "Frequency-response masking approach for the synthesis of sharp linear phase digital filters," IEEE Trans. on Circuits and Systems, vol. CAS-33, pp.357–364, Apr 1986.

[3] H.-J. Kang and I.-C. Park, "Pairing and ordering to reduce hardware complexity in cascade form filter design," ISCAS, vol. 4, pp. 265–268, 25-28 May 2003.

[4] R. Hartley, "Sub-expression sharing in filters using canonic signed digit multipliers," IEEE Trans. Circuits Syst. II, vol.43-10, pp. 677–688, Oct 1996.

[5] McClellan, J.H., Parks, T.W., Rabiner, L.R.: A computer program for designing optimum FIR linear phase digital filters, IEEE Trans. Audio Electro acoust., AU-21 (1973) 506–526.

[6] Rabiner, L.R.: Approximate design relationships for low-pass FIR digital filters, IEEE Trans. Audio Electro acoust., AU-21 (1973) 456–460.

[7] Chen, S.: IIR Model Identification Using Batch-Recursive Adaptive Simulated Annealing Algorithm, In Proceedings of 6th Annual Chinese Automation and Computer Science Conference, 2000, pp.151–155.

[8] Mastorakis, N.E., Gonos, I.F., Swamy, M.N.S.: Design of Two Dimensional Recursive Filters Using Genetic Algorithms, IEEE Transaction on Circuits and Systems-I; Fundamental Theory and Applications, 50 (2003) 634–639.

[9] Karaboga, N.: A new design method based on artificial bee colony algorithm for digital IIR filters. Journal of the Franklin Institute, 346(4), 2009, 328–348.

[10] Kennedy, J., Eberhart, R.: Particle Swarm Optimization, in Proc. IEEE int. Conf. On Neural Network, 1995.

[11] Eberhart, R., Shi, Y.: Comparison between Genetic Algorithms and Particle Swarm Optimization, Proc. 7th Ann. Conf. on Evolutionary Computation, San Diego, 2000.

[12] Ababneh, J.I., Bataineh, M. H.: Linear phase FIR filter design using particle swarm optimization and genetic algorithms, Digital Signal Processing, 18, 657–668, 2008.

[13] Ling, S. H., Iu, H. H. C., Leung, F. H. F., and Chan, K.Y.: "Improved hybrid particle swarm optimized wavelet neural network for modeling the development of fluid dispensing for electronic packaging," IEEE Trans. Ind. Electron., vol. 55, no. 9, pp. 3447–3460, Sep. 2008.

[14] Biswal, B. P., Dash, K., Panigrahi, B. K.: "Power quality disturbance classification using fuzzy C-means algorithm and adaptive particle swarm optimization," IEEE Trans. Ind. Electron., vol. 56, no. 1, pp. 212–220, Jan. 2009.

[15] Karaboga N, Cetinkaya1 B.: 'Design of digital FIR filters using differential Evolution algorithm,' Circuits Systems Signal Processing, 2006, 25, (5), pp. 649–660

[16] Liu G, Li YX, and He G.: 'Design of Digital FIR Filters Using Differential Evolution Algorithm Based on Reserved Gene', IEEE Congress on Evolutionary Computation, 2010, pp. 1-7

[17] Luitel B, Venayagamoorthy GK.: 'Particle swarm optimization with quantum infusion for system identification,' Engineering Applications of Artificial Intelligence, 2010, 23, (5), pp. 635-649

[18] Sarangi A, Mahapatra RK, Panigrahi SP.: DEPSO and PSO-QI in digital filter design,' Expert Systems with Applications, 2011, 38, (9), pp.10966-10973

[19] Luitel B, Venayagamoorthy GK.: 'Differential evolution particle swarm optimization for digital filter design,' IEEE World Congress on Computational Intelligence (IEEE Congress on Evolutionary Computation), CEC 2008, pp.3954-3961

[20] Lin, Z.: An introduction to time-frequency signal analysis, Sensor Review, vol. 17, pp. 46–53, 1997.

[21] D. Mandal, S. P. Ghoshal, and A. K. Bhattacharjee, Application of Evolutionary Optimization Techniques for Finding the Optimal set of Concentric Circular Antenna Array, Expert Systems with Applications, (Elsevier), vol. 38, pp. 2942-2950, 2010.

[22] D. Mandal, S. P. Ghoshal, and A. K. Bhattacharjee, Comparative Optimal Designs of Non-uniformly Excited Concentric Circular Antenna Array Using Evolutionary Optimization Techniques, IEEE Second International Conference on Emerging Trends in Engineering and Technology, ICETET'09 (2009), 619-624.

[13] D. Mandal, S. P. Ghoshal, and A. K. Bhattacharjee, 'Swarm Intelligence Based Optimal Design of Concentric Circular Antenna Array,' Journal of Electrical Engineering, vol. 10, no. 3, pp. 30–39, 2010.

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